An investigation of Convolution Neural network and discrete wavelet transform for early effective classification and detection of Mesothelioma Cancer

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Abstract: The presence of pleural mesothelioma, a malignant tumour that is made up of mesothelial cells, has been related to asbestos exposure. Despite the availability of chemotherapy and a wide array of clinical inspections, accurate prognostication of pleural mesothelioma has proven to be difficult for patients as well as the medical personnel who are treating them. Pleural mesothelioma is the only person who has ever been identified as having this ailment. The diagnosis of mesothelioma may be challenging, and the expenses associated with making that diagnosis may quickly pile up. It is probable that a battery of tests that are not specific to mesothelioma will be conducted as the first stage in getting a diagnosis of mesothelioma. The imaging of the tumour, the collecting of a tissue sample, and the evaluation of the patient's blood are often included in the diagnostic procedures for mesothelioma. The use of deep learning has brought about a sea shift in the approach taken to solving issues that involve vast volumes of noisy, unstructured data. This article presents Discrete Wavelet Transform enabled AlexNet Convolutional Neural Network for disease marking towards accurate and detection of mesothelioma cancer.

Keywords: Pleural Mesothelioma; AlexNet Convolutional Neural Network; Discrete Wavelet Transform; Early Detection.

Introduction

A malignant tumour called pleural mesothelioma (PM) is made up of mesothelial cells and is related to asbestos exposure and is shown in Figure 1. As of the year 2015, the World Health Organization [1] recognises three different histological subtypes of mesothelioma, and these are epithelioid, biphasic, and sarcomatoid mesothelioma (MM). Despite the availability of chemotherapy [2] [3] and a wide array of clinical inspections, accurate prognostication of PM has proven to be difficult for patients as well as the medical personnel who are treating them. PM is the only person who has ever been identified as having this ailment. Because of the peculiarities of its biology, a definitive prognosis is difficult to arrive at, and the staging approach [4] that is used to diagnose it makes it difficult to determine what stage it is in at first [5] [6].

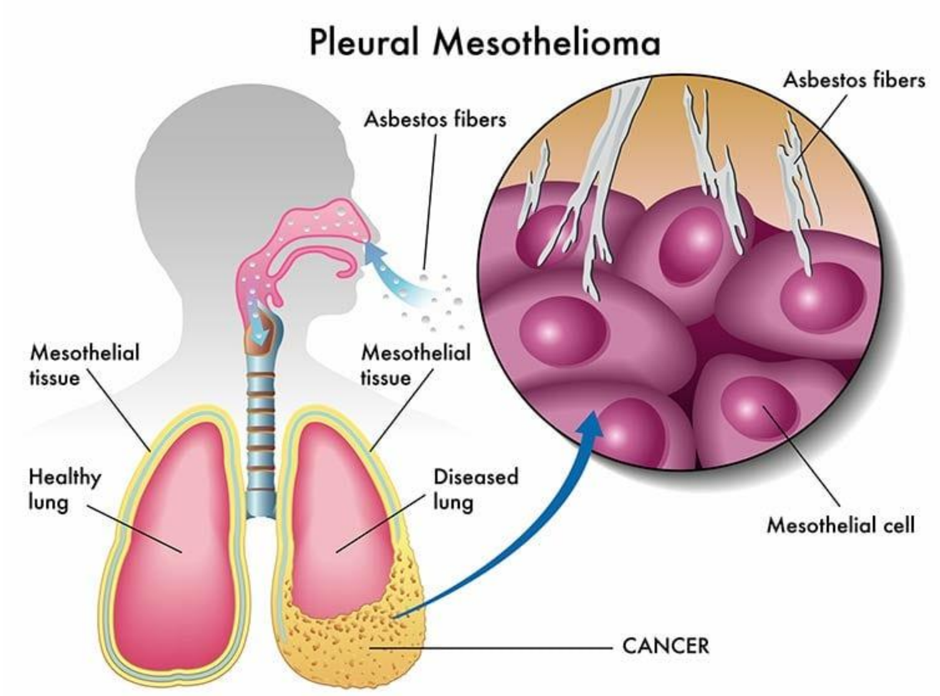

Figure 1: Mesothelioma Cancer

The diagnosis of mesothelioma may be challenging, and the expenses associated with making that diagnosis may quickly pile up. It is probable that a battery of tests that are not specific to mesothelioma will be conducted as the first stage in getting a diagnosis of mesothelioma [4]. This is because the initial step in making a diagnosis of mesothelioma is to eliminate less likely disorders. The relevance of certain diagnostic procedures is highlighted, in addition to the necessity of obtaining a second opinion. Because of these several contributing variables, it is possible that the cost of diagnosing mesothelioma would rise dramatically before any treatment has even been started. The imaging of the tumour, the collecting of a tissue sample, and the evaluation of the patient's blood are often included in the diagnostic procedures for mesothelioma [5].

Although methods for training machines have been around for quite some time, it is only very recently that researchers have discovered a way to successfully apply complex mathematical computations to enormous datasets. The processing power and storage capabilities of computers have continued to improve throughout the course of history. This has made it possible for machine learning algorithms to broaden their knowledge bases by analysing an increasing number and size of datasets. The use of deep learning has brought about a sea shift in the approach taken to solving issues that involve vast volumes of noisy, unstructured data. Because artificial neural networks can learn any function with just one hidden layer, regardless of how ambiguous the function may be, they are sometimes referred to as universal function approximators. This is because artificial neural networks can learn any function, regardless of how ambiguous the function may be. Those who have sufficient computational power and storage capacity, for instance, may be able to develop deep neural networks. These kinds of networks are made up of several stacked layers of neural networks that are linked to one another. Deep neural networks, often known as DNNs, are a kind of artificial neural network that simulates more sophisticated neural networks by using many layers of simulation [6] [7].

Related work

According to Chang et al [8], data on a gray-level matrix of co-occurrence features was created by a modified probabilistic neural network. The findings of the study unquestionably demonstrated that. The primary hepatic border is localised, and a comprehensive description of its specific characteristics is provided. Although there are many different kinds of liver tumours, the most common ones are called hepatomas and haemangiomas. There are also many more. In the suggested approach for diagnosing liver disease, thirty liver specimens will be used. A revolutionary method of categorising that goes by the name detect-before-extract is responsible for the recognition and extraction of the CT liver boundary in a mechanical fashion. This technique is sometimes referred to by the name "detect-before-extract."

An ultrasound picture of liver disease was analysed by [9] in order to assess the effectiveness of various image processing techniques. Feature extraction, feature selection, and classification were some of the procedures that were included in these approaches. The findings of this research provide support to the concept that GLCM is a widespread characteristic of the granularity and heterogeneity of liver tissue on a global scale.

According to the findings of Amiya Halder and colleagues [10], fuzzy hopfield neural network clustering facilitated the simplification of the formation of a genetic algorithm (GA) population and produced high-quality image segmentation in a relatively short period of time. The ability to segment images is now possible as a result of this and GAs. This method eliminates the need for human intervention by making it possible to carry out automatic segmentation of grayscale pictures into the bits that make up such images. The end goal of the technique is to produce a reliable segmentation of pictures based on data about intensity and neighbourhood relationships. This will be accomplished in the long run.

An evolutionary method to the construction of recurrent neural networks is investigated in great detail by Peter Angeline and his coworkers [11]. Both the genetic algorithm (GA) and evolutionary programming are examples of population-based search strategies that have been shown to be effective in very difficult environments. A "class" of designs has been generated as a result of established procedures for inferring the topologies of recurrent neural networks and the values of the weights that correspond to them. These designs are universally accepted for each application because they have been generated using these procedures. An evolutionary programme that can learn both the structure and weights of recurrent networks concurrently is suggested in this article. This programmed evolutionary approach is offered as an alternative to the GA, which is claimed to be an insufficient instrument for the job at hand. The authors of this study contend that the GA is not the most efficient tool for performing this job, despite the fact that it has been used to a large extent for this purpose.

In a comprehensive study that Shafaf Ibrahim et al [12] conducted, they presented three distinct methods: the Seed-Based Region Growing technique, the Adaptive Network-Based Fuzzy Inference System paradigm, and the Fuzzy c-Means (FCM) method. These three methods are all different ways of approaching the same problem. When compared, these three approaches provide potentially fruitful lines of inquiry that should be pursued in relation to the classification of luminous aberrations. There is not a single circumstance in which we have seen a performance of a dark anomaly segmentation that generates a correlation value with even a minor amount of significance. As a result of these considerations, the segmentation of dark anomalies is now done with a level of precision that is lower than that of lighter anomalies.

Havaei [13] recommended making use of networks that may be adapted to low- and high-grade glioblastoma pictures obtained from MR scans. They demonstrated an innovative and different CNN design that may be used for computer vision. This was done by them as a component of their presentation. In order to do this, they investigated a cascade architecture, which is characterised by the fact that the output of one CNN is fed into the input of another CNN, the latter of which is the one that is used the majority of the time. The amount of time necessary to get a passing result on the 2013-BRATS test dataset may be greatly cut down using this method. A novel facet of the CNN concept is that it suggests a route design that is able to pick up on localised brain area characteristics in addition to ambient inputs. This is an important innovation. This contributes to the idea's originality as a result. When adopting the two-phase tracking technique suggested by the author, it has been shown that dealing with divergent labelling distributions is an easy task to accomplish.

Papik et al. [14] conducted a literature review covering the previous five to six years in order to provide a concise introduction to the topic. The review focused on the papers that are most relevant to the debate and provided examples of how neural networks may be used in medicine. The review was conducted in order to provide a concise introduction to the topic. They looked at a few different medical situations in order to have a better understanding of the problem of research into the applications of neural networks. It is essential to emphasise the fact that the use of this innovative technology will hasten the production of diagnostic tools that are at the forefront of their fields in terms of gastrography, electrocardiography, and microscopy.

In his paper [15], Muhammad Imran Razzak investigated current advancements in the architecture of deep learning and its optimization for the segmentation and classification of medical images. This article presents a comparison of a wide variety of different deep learning model architectures. They discussed some of the challenges that are encountered when using deep learning to medical imaging. They discovered that deep learning has its own special challenges, such as a lack of data, privacy and legal problems, the need for highly skilled medical workers, atypical data and ML methodologies, and a great deal more besides. Deep learning, on the other hand, has shown to be an effective strategy for overcoming challenges of this kind. The so-called "black-box issue" occurs when the building of a neural network is straightforward but it is impossible to specify how the needed output was achieved. The deep learning technique is also notable for its level of complexity and has gained widespread acceptance within the academic world while receiving little to no criticism. Since anyone is able to make a contribution to this area of research, a large number of institutions, including some of the most prestigious educational establishments, healthcare facilities, and information technology businesses in the world, are working together to locate the most effective solution for medical imaging on a global scale.

Methods

CT scan related to malignant pleural mesothelioma is pre-processed to remove noise using Discrete Wavelet transform. Preprocessed images are classified by AlexNet CNN.

A generalization of the Fourier method, the discrete wavelet transform [20] is commonly used in various a signal and image processing applications. The transformation of the wavelet is a mathematical tool that decomposes a signal into a representation demonstrating the details and patterns of the signal as a function of time. This interpretation characterizes transient events, eliminates noise, compresses data and executes many other operations. The DWT has been introduced as a highly efficient and flexible method that is used in JPEG2000, to compress still images. Due to their large contrast of neighboring pixel intensity values, bio-rthogonal wavelets are widely used in image processing to detect and filter white Gaussian noise. Using these wavelets, a wavelet transform is performed on the two-dimensional images.

Convolutional Neural Networks (CNN) or ConvNets are a class of deep neural networks algorithm that was introduced in 1996 by Yann LeCun and Yoshua Bengio [16]. In recent years CNN has made rapid progress in the field of computer vision. Images are recognized by humans and animals by representing them as a grid pattern, CNN is inspired by this and is designed in such a way that it can adaptively and automatically learn hierarchies of spatial features from the high level to lowest patterns exhibited. Convolutional Neural Network (CNN) has three main building blocks namely Convolutional Layer, Pooling Layer, Fully Connected Layer. It's encoder is shown below in Figure 2.

Feature extraction is performed by the Convolutional Layer and pooling layer while the fully connected layer maps the features extracted by the above two layers into the final output [17]. It is a CNN designed by Alex Krizhevsky and his team, AlexNet is also the first CNN model to leverage GPU for improving the training efficiency. AlexNet is the winner of the 2012 ImageNet challenge and is single headedly responsible for invoking interests and research in the working of CNN and DL. Before AlexNet image classification models had an error rate of about 25% AlexNet 's error rate was only 15.3% enabling it to clinch the title as the winner of the ImageNet (ILSVRC) challenge 2012. AlexNet is made of 5 convolutional layers, 3 max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer. The convolutional layers have convolutional filters and ReLU is the activation function employed. Max Pooling is performed in the pooling layers. AlexNet accepts inputs of fixed size of 227x227x3. AlexNet has Sixty million parameters and 650,000 neurons.

Proposed system includes hybridization of DWT and AlexNet for precise and initial stage detection of PM (Figure 3).

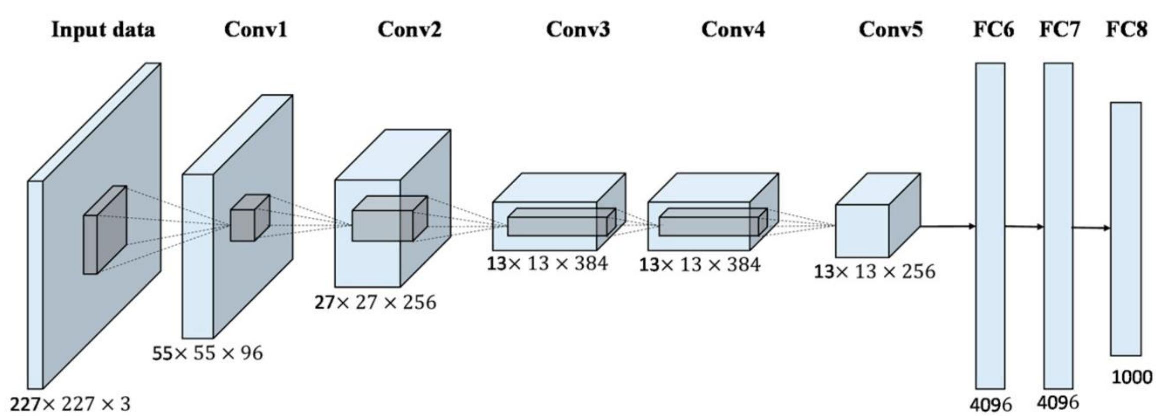

Figure 2: Architecture of AlexNet

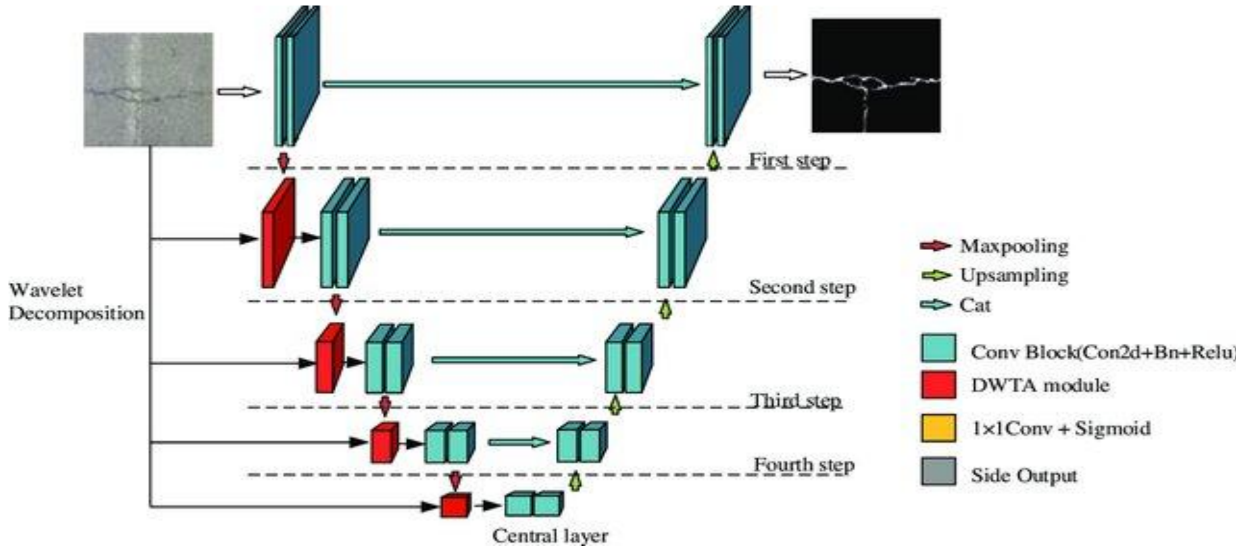

Figure 3: Architecture of Hybrid DWT and AlexNet

Conclusion

Asbestos exposure has been linked to the development of pleural mesothelioma, a malignant tumour generated by cells found in the lung lining. The availability of chemotherapy and many clinical tests has not made it easier for patients or healthcare providers to predict PM accurately. This illness has so far been associated only to PM. Mesothelioma diagnosis may be difficult, and costs can quickly climb. Initially, a battery of non-specific tests will most likely be used to identify mesothelioma. Tissue sample, blood analysis, and tumour imaging are common diagnostic procedures for mesothelioma. The use of deep learning has triggered a paradigm change in the approach to problems requiring massive amounts of noisy, unstructured data. The goal of this research is to identify and properly classify mesothelioma cancer using a Discrete Wavelet Transform-enabled AlexNet Convolutional Neural Network.

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